Spectroscopic Image Signature Classification of Land Cover Types using Multi-Spectral Data within a Neural Network

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Abstract—Through improvements in technology, high resolution multi-spectral imaging allowed new capabilities to become available in the remote sensing field. Spectral signature classification technologies existed in the chemical spectroscopy field to identify minerals by way of active systems [1]. The theory of this paper surrounded the premise that passive systems can provide spectral signatures of objects within images from satellite platforms. Specifically this paper targeted land cover types from the Kittyhawk, North Carolina area. Multi-spectral signals presented up to seven individual readings per pixel. As the decision support system, a neural network was trained to decide the type of land cover based on the band readings. In an effort to determine specific land cover types based on need, ground truthed spectral readings were also classified using a linear model to convert the readings into approximate satellite readings. The converted readings were then classified by the trained neural network. A minimal r-squared valued of 86% was required to be considered a viable method of image classification.

Index Terms—Artificial neural networks, Hyperspectral imaging, Spectroscopy, Feedforward neural networks, Multispectral perceptrons, Neural networks, Uniform resource locators, Random Access Memory, Software

I. INTRODUCTION

Remote sensing is the science of obtaining information about objects or areas from a distance, typically from aircraft or satellites. Current methods for classifying land cover types over large areas are limited to allow data to be acquired in repeatable manners [2]. Information derived from imagery attained in remote sensing is then applied to coastal, ocean, hazard assessment, and natural resource management fields [3]. Although, many Americans and scientists globally rely on the potential in remote sensing, remotely sensed imagery is often viewed as too low for operational user [2]. A myriad of key factors play into the problems encountered in remote sensing. These problems include but are not limited to the nature of classes, the spatial and spectral resolutions of the remote sensor used, classification methods, and the nature of Je'aime Powell, Mentor Elizabeth City State University 1704 Weeksville Road, CB 672 Elizabeth City, NC jeaime.powell@cerser.ecsu.edu

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the land cover mosaic [2].

The development procedures of collecting and analyzing remotely sensed data have been altered changed, and improved upon by scientist globally for more than 140 years [4]. Currently, the remote sensing process includes the statement of the problem, data collection, data analysis, and presentation of the information so that recommendations and informed decisions can be made [4]. Remotely sensed data is only collected using passive and active sensors. Passive sensors record "...naturally occurring electromagnetic radiation that is reflected or emitted from the terrain" [4]. Examples of passive sensors may include digital sensors and video sensors that are able to detect and record near- infrared energy reflected from the terrain. Active sensors like sonar and radar "... bathe the terrain in man-made electromagnetic energy and then record the amount of radiant flux scattered back toward the senor system" [4].

Remote sensing systems have four known major resolutions associated with them including sensor, spectral, spatial, and temporal resolutions. Resolution refers to the resolving power and is defined as a measure of the ability of an optical system to distinguish between signals that are spatially near or spectrally similar [4]. Spectral resolution refers to the dimension and number of specific wavelength intervals in the electromagnetic spectrum to which a remote sensing instrument is sensitive [4]. Spatial resolution is a measure of the smallest linear or angular separation between two objects that can be resolved by the sensor [4]. Remotely sensed data seen through spatial resolutions are collected through aerial platforms. Satellites usually collect data using hyper-spectral or multi-spectral spectral resolution. Multi-spectral remote sensing refers to the collection of reflected, emitted, or backscattered energy from an object or area of interest in multiple bands of the electromagnetic spectrum [3]. An example of a satellite that uses multi-spectral remote sensing to collect data is Landsat. Hyper-spectral remote sensing involves data collection in hundreds of bands [4] [5]. An example of a satellite that uses hyper-spectral data collection methods is the GEOEYE satellite [3]. When comparing hyperspectral and multi-spectral imaging in remote sensing, hyperspectral images will always stand as the victor. Hyper-spectral remote sensing images possess a very high spectral resolution allowing researchers to obtain higher data accuracy. Multispectral remote sensing images collected for data analysis possess relatively low spectral resolutions. The most precise and accurate data cannot be obtained through multi-spectral data retrieved by a satellite.

Imaging and classification are key factors in the field of remote sensing. Imaging is also one of the main sources of how remotely sensed data is analyzed and presented. The resolutions of a sensor used to collect images during investigations in the remote sensing field are crucial to the precision and accuracy of data collected. The shutter speed and aperture size of the sensor used is also crucial in collecting accurate data. The shutter of a sensor refers to the exposure time or the length of time a sensor's shutter is open to receive light from an image. In image classification, support vector machines have been shown the most reliable in multivariable cases [2]. Through thresholds, binary decision trees were easily defined; although, a significant amount of data was removed to make assumptions [6]. One paper did however elude "in view of the benefits and limitations of each, the neural network approach is recommended for future consideration" [7] [4]. Guidelines to the creation of such networks including network weight, learning rate, momentum term, and the number of hidden layer nodes have also been presented [4] [8]. This project used a multi-layered perceptron neural network, which was a function within WEKA. WEKA is a decision support software package that was used to classify between different land cover types. WEKA is a workbench for machine learning that is intended to aid in the application of machine learning techniques to a variety of realworld problems, in particular, those arising from agricultural and horticultural domains [8]. WEKA provides a wealth of interactive tools for data manipulation, result visualization, database linkage, and cross-validation and comparison of rule sets, to complement basic machine learning tools [8]. A neural network is computer or computer software modeled after the human brain and nervous system. Artificial intelligence neural networks abstract the complexity of the brain and nervous system and focuses solely on the information that it is processing at a given time [9]. The multi-layer perceptron function of the neural network used during the duration of this investigation was a feed forward neural network model that mapped out a set of input data onto a set of appropriate output [10] [11].

The investigation discussed within this paper surrounded if spectral signatures can be used to classify land cover types through the use of a neural network? In addition sub questions include; [2] • How to develop a sensor platform housing lab spectral equipment enabling use for field work?

• What would be the best possible workflow to collect data using available equipment?

• What correlation exists between Landsat readings and spectrometer readings if any?

• How can a neural network be utilized to perform land cover classifications?

• Can a neural network classify land cover types with at least 86% accuracy?

II. METHODOLOGY

A. Delimiters

The following items limited the scope of the project conducted:

1) The project focused on the testing of only two land cover types for proof of concept (sand and grass).

2) The project did not include any mixed pixel land cover classifications.

3) Only multi-spectral data from the LandSat 7 satellite was utilized.

4) The ground truth data range was limited by the spectrometer to a reading of 65535 of illuminations.

5) Spectral readings were collected with the Spectrometer manufacture Ocean Optics provided software Spectral Suite version 6.1.

6) The machine was limited to Windows 32-bit due to Spectral Suite requirements.

7) The areas of interest (Jockey's Ridge's Sand Dunes and Wright Brothers' Memorial Park) were selected due to high availability of imagery.

8) Research permits were requested and granted at the target ground truth areas of Jockey's Ridge's Sand Dunes State Park and Wright Brothers' Memorial National Park [Appendix A and B].

9) Only three samples per 30mx30m pixel were taken.

10) Spectral samples were taken in "Scope Mode" per manufacturer instructions.

11) Calibration used was the factory default.

12) No spectral data was used from the webcam reference images for either neural network training or classification.

13) All samples were compared with the Landsat 7 imagery collected on 06/06/2012.

14) No image manipulation was performed to the level 1 GeoTIFF from Landsat 7 in Exelis ENVI.

15) The GPS coordinate accuracy connected to the spectral readings was limited by public use GPS limitations.

B. Materials

1) Hardware

The tools that were gathered in order to complete the project included an Ocean Optics Spectrometer USB4000 used to ground-truth the spectral readings from the sample points. A CREATIVE Live Cam Socialize HD Webcam was used for reference image capturing to make insure the data visually matched the spectrum collected by the spectrometer. A Garmin Global Positioning System (GPS) 60CSx device was used for data geo-referencing. Other tools utilized were an ASUS Eee PC Laptop which housed all of the data initially from the attached sensors, the spectator a sensor instrumentation platform for the field, and a Verizon Mifi card that was utilized for mobile Internet access in the field.

2) The Spectator Instrumentation Platform

A platform to house the sensors was designed to solve the problem of retrieving consistent data from the attached spectrometer. The platform's purpose was to properly hold the lab equipment while the data was that was needed could be gathered. The name chosen for the tool was The Spectator Instrumentation Platform or "The Spectator" in short. The process of designing the tool had several revisions before arriving at the final design. Action was taken in order to build "The Spectator" by gathering a two-by-four, a piece of plywood, a handle, a bracket, a brace, some Velcro, screws, and hooks. After "The Spectator" was built, documentation of the design was provided for the Creative Commons licensing {Appendix C}. To properly test and utilize the tool, the sensors were mounted to test for stability and maneuverability. Actions were then taken to upgrade "The Spectator" for better data collection and easier mobility, which included the addition of a second handle, a hood and an umbrella for easier viewing of the laptop screen in direct sunlight. The lower portion of The Spectator (Figure 1) was painted matte black to reduce unwanted refection of irrelevant light sources.



Fig 1. The figure above displays the design of "The Spectator" and the matte black paint that surrounded the bottom of the tool.

3) Software

In order to use the attached sensors, applications were installed for data collecting and data transfer. The operating system required was Windows 7 (32-bit) due to software limitations stemming from Ocean Optics SpectaSuite v6.1. To utilize the GPS system, Google Earth was installed and set to receive data from a Garmin product. Many webcam applications were tested, including Fwink, Gimp, AMcap, LiveCam, E-Cam, and finally Creative Live! Central 3. Other

applications installed included the software KMLCSV Converter 2.2.0 by Choon-Chern Lim, Exelis Environment for Visualization Images (ENVI) 5.0 and the University of Waikato's Waikato Environment for Knowledge Analysis (WEKA). In order to share and enter data effectively, a Google Drive account was opened and a Google Spreadsheet was created. A Google Picasa account was opened in order to utilize the universal resource locater (URL) to access the reference images taken with the samples from within the spreadsheet.

C. Initial Workflow

The initial workflow consisted of both field and laboratory methods. The team also associated the term "pixel" with the 30mx30m area of a Landsat image pixel, and "sample" with a spectral collection point within the pixel (i.e. there were five samples within a pixel). In the field, Ocean Optics SpectraSuite was used to both collect and save the spectral bands termed illumination into tab delimited text files. Google Earth Version 6.2.2.6613 was utilized to mark GPS coordinates for the sample areas. The webcam application used to capture the reference picture was named Fwink. In the laboratory, the initial workflow consisted of adding collected band data into a spreadsheet record with associated imagery and GPS location.

1) Workflow Issues

Initial field testing found the workflow to fail, because the webcam software had both poor resolution and file naming was troublesome. The collected spectral files could not be accessed outside the SpectraSuite software nor could the raw readings be accessed. There was also an issue wherein the reading from the SpectraSuite maxed out when collecting a sample. The GPS coordinates within Google Earth were also found to not track new sample points when marking locations. Lastly, there was no standard file system to organize collected data.

D. Adjustments and Solutions

Before deciding on a final workflow, issues that arose within the workflow were addressed. In short, saving the spectrum readings proved to be problematic and incorrect, finding webcam software that would allow picture identification at a reasonable resolution was a challenge, and taking accurate GPS readings from Google Earth was unreliable. The SpectraSuite software was configured to save spectral readings into a tab delimited text file as opposed to the proprietary format that was default. To correct the spectral readings maxing out, the "integration time" was reduced from 1000ms to 50ms. This effectively reduced the shutter speed of the senor, thereby reducing the amount of light collected in a sample. The collected sample luminance ranged from 0 to 65535. The webcam application issues were resolved two in two ways. First the factory default was installed with time stamping turned on. Secondly the organizational file system created by the team allowed images to be saved by pixel into

sample area folders. The GPS coordinate issue was resolved by using the device to mark locations in decimal format. The marked waypoints were then downloaded into Google Earth after collecting all samples from target pixels at a location. Computer OS updates occurring at random times during the process also plagued the team in the field. This issue was resolved by turning automatic updates off from within Windows 7.

Additional problems that occurred included find a method to import the reference images into the master Google spreadsheet. To comply with Google link needs, a Google Picasa account was created to hold the reference images. Web links from the images were then used in combination with the "=image" cell function. For a file system, folders were created with names that signify what specific pixel based on the number, and the location (i.e. Jockey's Ridge or Wright Brothers Memorial).

In the laboratory, a question surrounding how to extract band data from the Landsat data retrieved from the United States Geological Survey Global Visualization Viewer (GLOVIS) arose. Imagery from GLOVIS was available in Geostationary Earth Orbit Tagged Image File Format (GeoTIFF). The solution for this problem included using Exelis ENVI 5.0 to view the geotiff files. The "GoTo" in combination with the "Cursor Value" functions within the application would then present the wanted band data in brightness values ranging from 0 to 255. Collected data was then entered into the Google Spreadsheet records by geolocation and band. The final issue that was faced was the Universal Serial Bus (USB) ports having issues detecting the equipment consistently. In order to solve this problem, the USB cables of the devices were designated specific USB ports on the laptop for the duration of the project.

E. Final Workflow

1) Field Work

At the first field sample location was considered pixel one at zero meters. After that, two more sample points were taken from that pixel at thirty-two meters and sixty-four meters linearly. At the last point in the pixel, one-hundred thirty-two feet was measured from that pixel to the next pixel, and the process repeated for the collection of the remaining sample points.

Spectral readings were taken from two locations in North Carolina, including the Sand Dunes of Jockey's Ridge and the fields of the Wright Brothers' Memorial Park. In order to have access of the public land areas, research permits were requested, completed, and presented to the respective park rangers at each location {Appendix A and B}. The spectral readings were saved as tab delimited files with an integration time of 50ms within the "spect" sub-folder of the pixel folder within the file system. The coordinates were marked on the GPS device in decimal format and later transferred to Google Earth. The reference image of the sample location was lastly

taken. The images were saved with a timestamp within the "pict" sub-folder of the pixel folder within the file system.

2) Laboratory Work

These GPS coordinates imported into Google Earth from the GPS device were saved in keyhole markup language (KML) file. The KML file was then entered into an application named KMLCSV Converter, to export the decimal values of the GPS coordinates into a comma separated values (CSV) format. Landsat GeoTIFF imagery was retrieved from the USGS Global Visualization Viewer (GLOVIS) website. These Landsat images were then opened in ENVI to gather the pixel band data. In this specific case, four different bands of the possible seven readings were recorded for each pixel. This limitation occurred because the lab spectrometer's upper wavelength limit was 65535 illuminant readings. The data was then entered into the master Google Spreadsheet document.

III. ANALYSIS

The maximum value from the range of each of the four bands was taken from the spectral files [12]. In combination with the Landsat readings, the spectral data was imported in to a Microsoft Excel spreadsheet to perform a linear regression by band. The first linear regression (Fig. 1) performed was on the data collected from Band, "blue, 0.45 - 0.52 micrometers [13]," and produced a r-squared value of 88.51%, which in turn supplied the conversion equation, "Equation 1," which was:

where B1 was the spectral readings of Band 1 and Landsat B1 was the converted Landsat reading of Band 1. The second linear regression (Fig. 2) was conducted utilizing data from Band 2, "green, 0.52 - 0.60 micrometers [13]," and produced an r-squared value of 88.77%, which in turn supplied the conversion equation, "Equation 2," which was:

where B2 was the spectral readings of Band 2 and Landsat B2 was the converted Landsat reading of Band 2. The next linear regression (Fig. 3) was attained by acquiring data from Band 3, "red, 0.63 - 0.69 micrometers [13]," and produced a r-squared value of 91.06%, which in turn supplied the conversion equation, "Equation 3," which was:

where B3 was the spectral readings of Band 3 and Landsat B3 was the converted Landsat reading of Band 3. The last linear regression (Fig. 4) was attained by the data collected for Band 4, "near infrared, 0.76 - 0.90 micrometers [13]," and produced an r-squared value of 34.53%, which in turn supplied the conversion equation, "Equation 4," which was:

Landsat B4=.0042*B4+23.26

where B4 was the spectral readings of Band 4 and Landsat B4 was the converted Landsat reading of Band 4. The conversion equations were then used from the linear regressions to convert the spectral readings (which range from 0 to 65535) of the sample locations to Landsat brightness readings (which range from 0 to 255) so that the neural network would be able to classify converted spectral readings as the correct classification.

To utilize the multi-layered perceptron neural network, an arff file had to be created to input the data into WEKA. The arff file consisted of what subject the file was related to, the different attributes that make up the arff file, and the data that was going to be used by the neural network to classify the land cover types. The goal was to utilize the multi-layered perceptron neural network in WEKA to classify land cover types using the data entered with 86% accuracy [14].



Fig 2. The image above displays the type of thermal bands and the wavelength, in micrometers, that correlate with the bands.



Fig 3. The above figure was a graph showing the correlation between the Spectrometer B1 Illuminants to Landsat Brightness Values. The graph displayed the trendline, r-squared value, and the function between the two datasets.



Fig 4. The above figure was a graph showing the correlation between the Spectrometer B2 Illuminants to Landsat Brightness Values. The graph displayed the trendline, r-squared value, and the function between the two datasets.



Fig 5. The above figure was a graph showing the correlation between the Spectrometer B3 Illuminants to Landsat Brightness Values. The graph displayed the trendline, r-squared value, and the function between the two datasets.



Fig 6. The above figure was a graph showing the correlation between the Spectrometer B4 Illuminants to Landsat Brightness Values. The graph displayed the trendline, r-squared value, and the function between the two datasets.

IV. CONCLUSIONS

How to develop a sensor platform housing lab spectral equipment enabling use for field work? An instrumentation platform named "The Spectator was constructed in order to house the lab spectral equipment for field work.

What would be the best possible workflow to collect data using available equipment? The best possible workflow for data collection was to save the spectrum as tab delimited files, take time and date stamped reference images, mark the GPS coordinates on the Garmin GPS systems, import those coordinates into Google Earth and convert those save files using the KMLCSV Converter Software, and use Exelis ENVI 5.0 to gather the Landsat band data utilizing the GPS coordinates. Lastly, Google Spreadsheet was utilized to enter in the data, and Microsoft Excel was utilized to perform a linear regression on the datasets to convert the Spectrometer Illuminants Values to Landsat Brightness Values.

What correlation exists between Landsat readings and spectrometer readings if any? The correlation that exists between Landsat readings and spectrometer readings was that the Landsat Brightness values, ranging from 0-255, correlated with the Spectrometer Band Illuminants Values, ranging from 0-65535.

How can a neural network be utilized to perform land cover classifications? An arff file was created in order to feed the Landsat band data and the land cover classification types into the Multilayer Perceptron Function to classify the land cover types.

Can a neural network classify land cover types with at least 86% accuracy? Yes, a neural network can classify land cover types with at least 86% accuracy {Appendix D}.

V. FUTURE WORKS

Further development of a larger data set sample with varied land cover types is needed in order to exhaustively investigate the classification of land cover types using spectral signatures. Specifically mixed pixel classifications should be explored using the spectral signature technique. The lab spectrometer used limited the data, allowing sample readings to reach up to only four out of the seven bands that existed. Expanded spectral equipment should be obtained in order to carry out the investigation. Having access to Xband (hyper-spectral) high resolution data or writing an image grant far in advance of the investigation to achieve access to a high-resolution satellite in which to verify the spectral readings collected from the ground truth data is necessary for achieving truly unique spectral signatures. Development of a software macro or all inclusive application to cut down on data collection time is highly recommended. Developing a program that would take a picture and name that picture; take the spectral signature and name that spectral signature; and mark the GPS coordinate, name the GPS coordinate, and save the GPS coordinate as a KML (keyhole markup language) file would be invaluable to future researchers. Using a netbook or a full blown notebook with higher system specifications and minimal programs installed on the device is also highly recommended allowing for smooth and quick data collection.

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APPENDIX A

PERMIT NUMBER	R R	.12-	35
DATE ISSUED	6	25	12

North Carolina Division of Parks and Recreation

Scientific Research and Collecting Permit

Please print or type legibly. Incomplete or illegible applications will be returned.

1. Principal Investigator

Name: Jea'ime Powell

Institutional Affiliation: Elizabeth City State University

Address: 1704 Weeksville Road, Box 672

Elizabeth City, North Carolina 27909

Phone: _

E-mail: jeaime.powell@cerser.ecsu.edu

2. Project Director or Major Advisor (If Applicable)

Name:____

Institutional Affiliation:

Address: ____

Phone:

E-mail:

3. Park Unit(s) Where Research is to be performed: Jockeys Ridge: Sand Dumes

4. Research Schedule:	
Field work: Start Date 06/27/2012	Ending Date 07/27/2012
Total project: Start Date 05/29/2012	Ending Date 07/27/2012

5. Attach a Detailed Project Description. Include:

1. Resume/vita of the Principal Investigator and Project Director. If not apparent from your resume, briefly state your experience and qualifications in the area of proposed research.

2. A project synopsis, including purpose (graduate thesis, independent study, etc.), specific objectives and complete methodology. If applicable, include a species list and the name and address of the proposed curatorial facility. If your project involves ground disturbance, estimate the amount, location and duration.

3. Clearly marked USGS topographic maps (1:24,000) or park brochure maps showing proposed study areas. USGS maps must show the quad name. For information on USGS maps, contact the N.C. Geological Survey Sales Office at (919) 715-9718.

4. A list of other required permits and proof of possession.

NOTE TO THE APPLICANT:

The permittee must notify the park superintendent prior to initiating any research activities. This permit may be used only by the person(s) to whom it is issued. Principal investigators will provide the division with two copies of a research report within 60 days of the project's conclusion and two reprints of any publication resulting from studies conducted on state park property. An annual report, due on January 31, is required for any project exceeding one year. Reports are to address the project's goals, methodology, results and conclusions. Progress reports may also be specified as a condition of the permit. The reporting requirement may be waived for classes that use a park as an outdoor classroom.

This permit is issued subject to the conditions specified below:

The permittee shall and hereby does waive and release any and all claim against the North Carolina Department of Environment and Natural Resources, or its employees, or the State of North Carolina for any and all damages, loss or cost to person or property arising either directly or indirectly from the use of said premises and/or from the exercise of the privileges granted by this permit.

Signature of Principal Investigator/Date

FOR ADMINISTRATIVE USE ONLY

Date Received: 6/25/2012		0/
Approved by: Scott Cotfman Acting	Superintendent	Sest allow
Staff Coordinator: Justin Bannes Park	Rangen	
Comments/Conditions:		

APPENDIX B

COLLECTIO	G PERMIT	Study#: WRBR-00007 Permit#: WRBR-2012-SCI-0001 Start Date: Jun 25, 2012			
Grants permission in acco	rdance with the attached				
general and spec	national of the Interior	Expiration Date: Dec 31, 2012			
Viited States De Nation	al Park Service	Coop Agreement#: n/a			
Wright	t Brothers NM	optional Fait Codel ma			
Name of principal investigator:	2				
Name: Jeaime Powell Phone: 2	2523358524 Email: jeaime.p	owell@cerser.ecsu.edu			
Name of institution represented:	C. C				
Elizabeth City State University					
Co-Investigators:					
Name: Bernard Aldrich Jr.	Phone: 2523353696	Email: trillster@yahoo.com			
Name: Charniece Huff	Phone: 2523353696	Email: chuff3@scmail.spelman.edu			
Project title:					
Spectroscopic Image Signature Cl	assification of Land Cover Ty	pes using Multi-Spectral Data within a Neural network			
Purpose of study: Through improvements in technol available in the remote sensing fie identify minerals by way of active passive systems can provide spect	ogy, high resolution multi-spe eld. Hyper-spectral technolog systems (Green et al., 1998). ral signatures of objects with	ectral imaging have allowed new capabilities to become ies have existed in the chemical spectroscopy field to The theory of this paper surrounds the premise that n images from satellite platforms. Specifically this paper			
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ANY COMMERCIAL OR FOR-PROFIT ACTIVITY IS PROHIBITED WITHOUT THE EXPRESS PERMISSION OF THE SUPERINTENDENT FOR THE OUTER BANKS GROUP.

Please read and understand enclosed NPS guidelines and park guidelines. Failure to submit an Investigator Annual Report (IAR) will result in the termination of this permit. Please address any questions or concerns to the address below. At conclusion of the study a copy of the final report including study locations, research methods, collected data, and results should be sent to:

Sara Strickland, Research Permitting Coordinator

National Park Service - Outer Banks Group

1401 National Park Dr.

Manteo, NC 27954

Sara_Strickland@nps.gov

252-473-2111 ext 142

THIS PERMIT DOES NOT AUTHORIZE RESEARCHER ACTIVITY BEHIND CLOSED GATES OR IN RESOURCE CLOSURES UNLESS ACCOMPANIED BY PARK STAFF.

PARK SPECIFIC CONDITIONS

(1) This permit required that specific INFORMATION ON RARE OR SENSITIVE RESOURCES ACQUIRED DURING THE COURSE OF RESEARCH CANNOT BE RELEASED WITHOUT PRIOR APPROVAL FROM THE NATIONAL PARK SERVICE. Your work at the park makes you an agent of the National Park Service, and requires you to keep confidential any protected information that you develop or otherwise acquire as part of your work for the Park Service. By law, you cannot share protected information with anyone through any means except as specifically authorized by the National Park Service. Protected information concerns the nature and specific location of endangered, threatened, rare, commercially valuable, mineral, paleontological, or cultural patrimony resources such as threatened or endangered species, rare features, archeological sites, museum collections, caves, fossil sites, gemstones, and sacred ceremonial sites. This prohibition applies to inadvertent disclosure of such information through websites, maps, scientific articles, presentations and speeches.

(2) All collecting/research must be done away from roads, trails, and developments unless otherwise specified in the permit. Collection methods shall not attract attention or cause damage to the environment. Any disturbance in excess of one square meter shall be rehabilitated to the satisfaction of the Superintendent prior to completion of this project. Access trails shall be brushed in; natural contours shall be reestablished; soil scarified and mulched.

(3) Retain a copy of the Outer Banks Group Standard Operation Procedures document entitled "Outer Banks Group Museum Procedure Checklist for Natural History Collections." This will be necessary if you collect, and expect to retain any specimens from the park.

(4) If designated parking areas are not convenient, park in a safe place with plenty of sight distance for other traffic that does not cause any damage to the resources.

(5) As mandated by Cape Hatteras National Seashoreâ s Off-Road Vehicle (ORV) Management Plan, everyone driving on the beach at the Seashore is required to have a beach driving permit, including those operating under a NPS research permit. In the event that you need to drive an ORV on the beach for your research, the park will provide this permit to you free of charge. To obtain an ORV permit, stop by one of our permit offices when you arrive, where you will need to present a valid driver's license, vehicle registration, and your current research permit. After watching a 7-minute orientation of your visit. If you will be making multiple visits to the Seashore throughout the year, you will need to stop by an office each time to pick up a new temporary permit, though you will not be required to go through the

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orientation again.

(6) Investigators may use temporary biodegradable surveyor-type flagging, standard aluminum tree tags, and nonreactive aluminum nails or marker stakes not taller than one meter as measured above ground level to mark a corner of the study area; landmark keys and/or field surveying procedures shall be used to reach plot sites. Stakes, flagging, and tags shall be indelibly stamped or marked with researcher's name, project name, and year-date. Unmarked plot markings are routinely removed by park personnel roving an area. Markers, when used, shall be located in areas not readily visible to visitors. All plot markings shall be removed at the conclusion of the study.

(7) Habitat disturbance associated with collecting specimen or conducting research can be very destructive, especially in headwater streams. Rocks, logs, etc., should be replaced as nearly as possible to their original position after collecting.

(8) No chemicals that result in the death of the specimen or which would permanently alter the habitat will be permitted, unless specimens are to be preserved for a collection or future dissection.

(9) Any collecting or research that will result in permanent changes or degradation of habitat is prohibited.

(10) No species collected from outside the park is permitted to be introduced or reintroduced into the park.

(11) At least one copy of all scientific and other publications resulting entirely or in part from research and/or collecting through the issuance of this permit will be furnished to the Superintendent of the park.

(12) To indemnify, save and hold harmless, and defend the United States against all fines, claims, damages, losses, judgments, and expenses arising out of, or from, any act or omission of the research permittee, its employees or representatives, arising out of or in any way connected to activities authorized pursuant to this Agreement. This obligation shall survive the termination of this permit.

(13) To cooperate with the NPS in the investigation and defense of any claims that may be filed with the NPS arising out of the activities of the cooperator, its agents and employees.

Recommended by park staff(name and title):

Reviewed by Collections Manager:

Sava Stockland - Research Fermitting Coordinator

Yes _____ No X

Approved by park official:

Date Approved: 6/26/12

pavel 3 Elos

Title:

Deputy Superintendent

I Agree To All Conditions And Restrictions Of this Permit As Specified (Not valid unless signed and dated by the principal investigator)

(Principal investigator's signature)

(Date)

THIS PERMIT AND ATTACHED CONDITIONS AND RESTRICTIONS MUST BE CARRIED AT ALL TIMES WHILE CONDUCTING RESEARCH ACTIVITIES IN THE DESIGNATED PARK(S)

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APPENDIX C

The Spectator Instrumentation Platform

Build Instruction Manual





Build Materials

- 2" x 4" board
- 2' x 1' x 3/4" Plywood board
- 10" shelf bracket
- 1.5" L bracket
- Velcro (Industrial Strength Recommended)
- Wood Screws (Steel 10 x 1)
- Nylon Clamps (5/8")
- 5 Rubber bands
- 2 x Utility pull handle
- Matte Black Paint

Required Tools

- Circular (Skill) Saw
- Power Drill
- Hole-saw bit
- Screw Driver
- Dremel w/ sanding bit (Optional)
- Safety goggles

Instrumentation and Sensors

- GPS (Manufacturer: Garmin)
- USB Webcam (Manufacturer: Creative Labs)
- Lab Spectrometer (Manufacturer: Ocean Optics)
- 11 inch Netbook with Windows 7 (32-bit) and minimum three (3) usb ports (Manufacturer: Asus)

BY SA
The Spectator Instrumentation Platform by Bernard Aldrich II, Charniece Huff, Je'aime Powell is licensed
under a Creative Commons Attribution-ShareAlike 3.0 Unported License.
Based on a work at nia.ecsu.edu.
Permissions beyond the scope of this license may be available at http://nia.ecsu.edu/reuomps2012/
teams/rs/research.html.

 $\Theta 0 0$

Software

- Google Earth (GPS)
- Spectra Suite (Spectrometer)
- Fwink (Webcam)
- KMLtoCSV Converter

Construction Instructions

1. Gather all materials and put on the safety goggles.

2. Cut the 2" x 4" board to a length that is comfortable for you using your circular saw and paint the board black (\sim 6' suggested).

3. Lay out all of your equipment onto $2' \times 1' \times \frac{3}{4}$ " plywood in order to decide where to make holes in the wood to mount your equipment



4. Mark the 2' x 1' x $\frac{3}{4}$ " plywood according to the size, amount, and arrangement of equipment and cut it to size with the circular saw.





5. Using a hole saw make circular holes into the $2' \times 1' \times \frac{3}{4}''$ plywood in order to mount your spectrometer, and webcam.



6. In order to protect your lab equipment use a Dremel w/ sanding bit (Optional) to smooth out any rough edges the Hole-saw bit left behind.

7. Determine a comfortable height at which you could attach the 2' x 1' x $\frac{3}{4}$ " plywood board to the 2" x 4" board that will allow you to operate your equipment comfortably in the field. (Suggested 16 $\frac{1}{2}$ " from the top of the 2 x 4)





9. Using a 10" shelf bracket and an 2" L bracket attach the to the 2' x 1' x $\frac{3}{4}$ " Plywood board to the 2" x 4" board securing it with wood nails.



10. Determine a comfortable height at which you can hold the 2' x 1' x $\frac{3}{4}$ " Plywood board in place while in the field and attach the handles onto the 2" x 4" board securing it with wood screws.





Sensor and Equipment Mounting

- 1. In order to protect your lab equipment in the field secure the laptop to the "Spectator" using Velcro. Place Velcro strips onto the second piece of wood vertically.
- 2. Place Velcro onto the bottom of your laptop horizontally.
- 3. Place small Velcro strips on the edges of the webcam circular hole
- 4. Place Velcro on the edges of your webcam
- 5. Secure your Lab Spectrometer (Manufacturer: Ocean Optics) by placing it into the hole drilled by your Hole-saw bit and secure it using rubber bands
- 6. The fiber to usb connection Spectrometer box must also be secured using rubber bands.
- 7. For cable management, screw plastic hooks to the appropriate sides of the Spectator.
- 8. Feed the cords from the webcam and Spectrometer through the hooks to keep them protected and secure while in the field.



APPENDIX D

Weka Results

=== Run information ===

```
Scheme:weka.classifiers.functions.MultilayerPerceptron -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a
          classification
Relation:
Instances: 80
Attributes: 5
       B1
       B2
       B3
       B4
       class
Test mode:evaluate on training data
=== Classifier model (full training set) ===
Sigmoid Node 0
 Inputs Weights
 Threshold -1.4748880863063045
 Node 2 4.369752148248364
 Node 3 3.260811969990686
 Node 4 -4.159347887173029
Sigmoid Node 1
 Inputs Weights
 Threshold 1.4975293238903364
 Node 2 -4.349909041745441
 Node 3 -3.306270338930676
 Node 4 4.137630706988339
Sigmoid Node 2
 Inputs Weights
 Threshold 1.8110756256663654
 Attrib B1 -1.9014491397674091
 Attrib B2 -2.045265392331165
 Attrib B3 -2.675176669356432
 Attrib B4 1.5238616886621446
Sigmoid Node 3
 Inputs Weights
 Threshold 1.358021733664664
 Attrib B1 -1.6406576395323467
 Attrib B2 -1.6768228129074665
 Attrib B3 -2.2140848377697457
 Attrib B4 1.1543858531401332
Sigmoid Node 4
 Inputs Weights
 Threshold -1.5374325516124607
 Attrib B1 1.6972594595421286
 Attrib B2 1.8552779591050168
 Attrib B3
           2.443202079986721
           -1.498702341733255
 Attrib B4
Class grass
 Input
 Node 0
Class sand
 Input
 Node 1
```

Time taken to build model: 0.47 seconds

=== Evaluation on training set === === Summary === Correctly Classified Instances 80 100 % Incorrectly Classified Instances 0 0 % Kappa statistic 1 Mean absolute error 0.0061 Root mean squared error 0.0086 Relative absolute error 1.2238 % Root relative squared error 1.7322 % Total Number of Instances 80 === Detailed Accuracy By Class ===

TF	P Rate	e FP	Rate	Precisio	on Re	call F-	-Measure	ROC Area	Class
1		0	1	1	1	1	grass		
1		0	1	1	1	1	sand		
Weighted A	Avg.	1	0	1	1	1	1		

=== Confusion Matrix ===

a b <-- classified as 44 0 | a = grass 0 36 | b = sand